As per UGC guidelines an electronic bar code is provided to seure your paper

International Journal for Modern Trends in Science and Technology, 9(07): 48-52, 2023

ISSN: 2455-3778 online
DOI: https://doi.org/10.46501/IJMTST0907007
Available online at: http://www.ijmtst.com/vol9issue07.html

Finding Uncovered Topical Centers and Authorities Represented by a Range of Social Media Platforms

B.Veerendra[1], Alekhya Jatla[2]

[1]Associate Professor, Dept of CSE, Kakinada Institute of Technology and Science, Divili, A.P
[2]PG Student, Dept of CSE, Kakinada Institute of Technology and Science, Divili, A.P
Email: veeru506@gmail.com[1], alekhyajatla1234@gmail.com[2]

To Cite this Article
B.Veerendra and Alekhya Jatla. Finding Uncovered Topical Centers and Authorities Represented by a Range of Social Media Platforms. International Journal for Modern Trends in Science and Technology 2023, 9(07), pp. 48-52. https://doi.org/10.46501/IJMTST0907008

Article Info
Received: 12 June 2023; Accepted: 05 July 2023; Published: 09 July 2023.

ABSTRACT

There is a significant challenge in identifying prominent users in OSNs uses in a variety of contexts. Various techniques have been presented for determining user community leaders in OSNs. The well-known cases of Page Rank and HITs identify key opinion leaders using link analysis. A number of recently developed models take into the material and the social media connections have been built up. Core Competency and Subject Matter Expertise the Hub and Spoke Analysis Toolkit Hub Authority Topic (HAT) is a model that builds on the HITS system by using learning communities, authoritative sources, and user-generated interest topics content. Many of the current studies, however, are restricted to only identifying important users. Amongst the nodes of the same OSN. Their inability to learn was directly related to the presence of many OSNs. People of note into one too generic category that ignores common themes and preferred media. Our plan is to compare MPHAT to current best practises in three areas: subject modelling, platform selection prediction, and link recommendation. With the help of MPHAT, an extension of HAT, we can model not just subject matter specialists but also those who often visit hubs dedicated to that topic, and their favourite platforms. Extensive experiments across different OSN environments, mostly with simulated data sets and the real-world Twitter and Instagram datasets, demonstrate that MPHAT can compete with and significantly outperform state-of-the-art classification techniques in learning topics within the context of platform prediction and link recommendation activities. We also provide actual evidence demonstrating MPHAT's capacity to locate central nodes in a network, whether it a single OSN or a collection of them.

Keywords: OSN,MPHAT,Twitter,instagram,HAT.

1. INTRODUCTION

Numerous OSNs, including social media sites like Facebook, Twitter, and Instagram, have seen meteoric rises in user engagement and popularity in recent years. Comparatively, as of August 2017 [1], Facebook has over 2 billion monthly active users, while Instagram and Twitter each had roughly 700 million and 300 million users. These platforms, with the vast volumes of data they create in the social and informational spheres, have become useful tools for marketing initiatives such as the distribution of advertising messages and the promotion of new products. That's why using OSNs to determine your most valuable customers is crucial for your marketing campaigns. Numerous research have offered advice on how to locate influential individuals on OSNs. In the literature [2, 3, 4, 5], many metrics of network centrality are addressed as a means of assessing a user's degree of influence inside a social group. To identify influential users in OSNs, several publications [8, 9, 10] have adapted methodologies like HITS [6] and Page Rank [7], which were originally created to identify hub and authority websites by analysing the link structure of a web graph. However, prior initiatives either don't focus on the problem at hand or can only identify key participants in a certain OSN. Investigating the profiles of the most prominent users on each OSN service will reveal which individuals have the most sway in that community. To demonstrate the benefits of topic specialisation, we will compare the ego networks of two users (u1 and u2) who are otherwise similar. HITS will rate u1_ and u2 as hubs and authorities in a similar fashion. This is because it is more likely that u1 and u2 are authoritative users on food-related and political subjects, respectively, if u1 is a well-known food content provider followed by many food-loving users and u2 is a well-known politician followed by many political-interested users. Expertise in the unique characteristics of OSNs is necessary for identifying important persons across networks. One user, u3, may be highly active in OSN p1 (where they post often about food and attract a large audience) but less so in OSN p2 (where they post frequently about other topics and attract a smaller audience) (where they post less content and create fewer connections). While u3's fame as a food business specialist in the OSN community is extensive, it is more in p1 than in p2. In order to be successful, applications like social sensing, viral marketing, and social recommendation must have users who are both influential and fundamental to the application's themes and interfaces. One possible solution to the cold-start issue in social recommendation [11] is to propose that a user u on a platform p follow other users on p who are highly authoritative on topics that u is interested in. A similar advertising strategy might include recruiting popular members of target demographics to assist disseminate campaign materials and boost brand awareness [12]. In order to stay abreast of social movements, you may choose to follow people who serve as hubs or authorities on a wide range of channels and topics [13]. Our mission is to back up those that serve as hubs for OSNs by becoming subject matter or platform experts. Applying existing topic-specific hub and authority models (for HAT [14]) to a large number of OSNs one at a time and then comparing the lists of top topical authority and hub users uncovered in each OSN is one simple approach to do this. It may be challenging to make meaningful comparisons between a user's hub and authority across OSNs if they study in isolation throughout the network. The issue of the incomparability of latent themes acquired from separate OSNs may be resolved by consolidating all of the existing OSN datasets into a single one from which subjects, hub scores, and authority ratings may be retrieved. To utilise HAT on a dataset consisting of user-generated posts and links from several OSNs, such as p1 and p2, it is necessary to merge the records from each of these sources into a single one. The method assumes that u always has the same hub and authority scores, which is a serious issue. In other words, if u is considered food-savvy on platform p1, she will also be considered such on platform p2. Still, there are situations when one medium outperforms the other. Therefore, we provide the Multiple Platforms Hub and Authority Topic (MPHAT) model, which simultaneously considers users' topical interests, platform choices, hub and authority ratings for particular themes, and all of these data. To start, we develop a system that can generate information and links for users across several OSNs automatically.

2. PROPOSED SYSTEM

Our research endeavours to create a model of OSN hub and authoritative users based on their knowledge base and chosen medium. Easy first steps include applying topic-specific hub and authority models (like HAT [14]) to many OSNs independently and then comparing the lists of top topical authority and hub users discovered in each OSN. Although it is possible to compare users' hub and authority across OSNs, doing so might be challenging due to the fact that people studied in isolation on various platforms may not be comparable. Merging datasets from these networks and then learning the users' subjects, hub, and authority ratings from the combined dataset is another possible method for overcoming the incomparability of latent themes collected from the various OSNs. We may join the post and link datasets from OSNs p1 and p2 and then apply the user's HAT on the combined dataset, as an example.

This method has a significant limitation in that it presumes that the hub and authority ratings on both platforms are identical. It follows that if u is acknowledged as a skilled cook on platform p1, she would be similarly acknowledged on platform p2. The statistics does not back up this supposition. We propose the MPHAT model to find users' subject passions, which we hypothesise may be more popular on one platform than another. Access to Subject-Matter Centers, System Experts, and More, Consolidated Into a Single Location. We begin by formulating a method for creating content and connections from the perspective of a broad range of OSNs and their users. Last, we detail MPHAT's parameter learning process. We conduct studies on real-world datasets as well as synthetic datasets to assess MPHAT. We run experiments on a real-world dataset to evaluate MPHAT on three criteria: I its ability to learn topics from user-generated content; (ii) its ability to predict the platform choice of users' publish post; and (iii) its ability to recommend topical influential users across platforms via link prediction in a multiple OSNs setting. We test MPHAT on synthetic datasets to see how well it can recover the topical hub and authority that users have curated for their respective platforms.

3. MODULE DESCRIPTION

OSN Server

In this module, the Service Provider must provide a valid login ID and password to access this section. Following a successful login, the user will be granted access to various features. These features include: viewing all users and authorising them, viewing friend requests and responses, viewing all user posts, viewing all recommended post details, viewing all hidden topic details, and viewing all score results for posts.

View and Authorize Users

In this module, When an administrator logs in, they will see a list of all users. Here, the administrator may see the user's credentials (such as name, email, and physical address) and provide access to the user.

End User

In this module, n is the total number of users. Users need to sign up first before they can do any actions. Individual information provided by users upon registration will be saved in a database. After his successful registration, he will be prompted to log in using his username and password. As soon as the user has successfully logged in, they will be able to do actions such as creating a profile, seeing other users and following those that interest them, checking out their friend recommendations, and perusing their own friend lists, among other things.

4. ALGORITHM

Step1.Let number of iterations be k.

Step 2.Each node is assigned a Hub score = 1 and an Authority score = 1.

Step 3.Repeat k times:

Step 4.Each node's Hub score =∑ (Authority score of each node it points to).

Step 5.Each node's Authority score =∑ (Hub score of each node pointing to it).

Step 6. In order to standardise the results, divide each Hub score by the square root of the sum of the squares of all Hub scores, and similarly normalise the Authority scores by the square root of the sum of the squares of all Authority scores.

5. PROPOSED SYSTEM ARCHITECTURE

In order to access the system, the Service Provider must provide a valid login name and password. Following a successful login, the user will be granted access to several features. These features include: seeing all users and authorising them, viewing friend requests and responses, viewing all user posts, viewing all recommended details, viewing all hidden topics, and viewing all score results. Users who have signed up may be seen by the administrator. Here, the administrator may check out data like the user's name, email, and physical address, and provide access to the users as needed. It's estimated that n people are now online. Users need to sign up for an account before they can do any actions. Upon successful registration, a user's information will be added to our database. To access the site after a successful registration, he will need to enter his username and password. After a successful login, users may do actions like as creating an account, seeing other users and following them, viewing their friend lists, adding posts, viewing their own posts, searching for posts, viewing the posts of their friends, and viewing recommended posts.

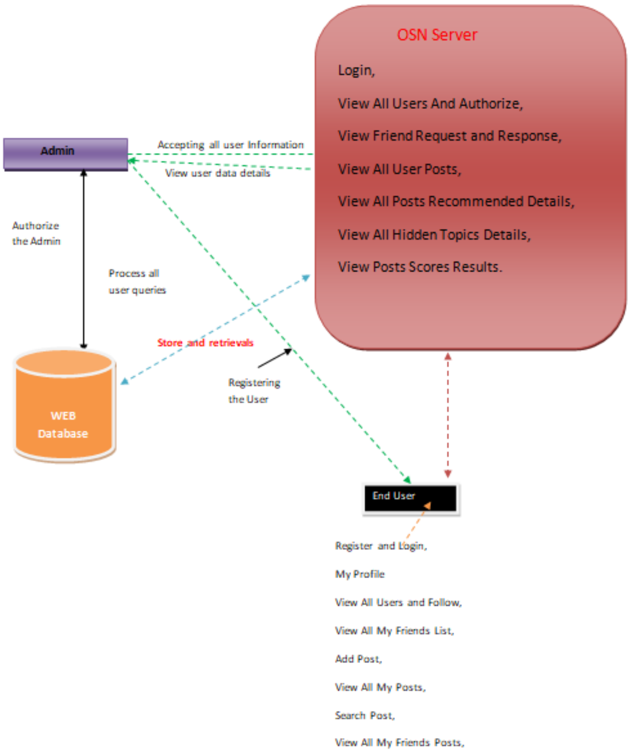

Fig1: Proposed System Architecture

6. EXPERIMENTAL RESULTS

Fig2: OSN Server Login

Fig3: OSN Server Home Page

Fig4: User Authorization

Fig5: User Home Page

Fig6: User Upload Posts

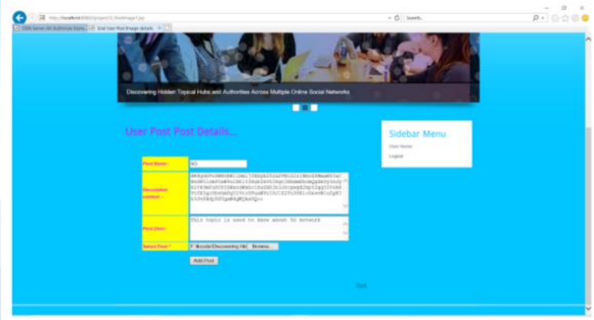

Fig7: User View Uploaded Posts

7. CONCLUSION

We introduce the Multiple Platform Hub and Authority Topic (MPHAT) model, a novel generative framework for modelling users' topic-specific hub authority, interests, and preferred platforms simultaneously. We tested MPHAT using both simulated and real-world data, and compared our results to the gold standard. We test our proposed MPHAT on Twitter and Instagram datasets and show that it outperforms LDA and achieves results on par with TW LDA in topic modelling. MPHAT beats the TW LDA baseline method when trying to predict where a user would share their content. MPHAT boosts MRR by 10% relative to the best existing link suggestion methods. The empirical results demonstrate that MPHAT can successfully identify authoritative sites on Twitter and Instagram across a broad variety of themes. We also show via simulated studies that our suggested model is superior to the reference technique in locating authority and hub users in many OSNs. Additional research is needed to include generic user interactions into our model. However, people may opt to follow one another for social as well as topical reasons, which is something we don't take into account in our current method (e.g., they are friends).

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

REFERENCES

[1] "Most famous social network sites worldwide as of august 2017,ranked by number of active users (in millions)," Statista, Tech. Rep., 2017.

[2] M. Cha, H. Haddadi, F. Benevenuto, and P. K. Gummadi, "Measuring user influence in twitter: The million follower fallacy." In ICWSM, 2010.

[3] E. Bakshy, J. M. Hofman, W. A. Mason, and D. J. Watts, "Everyone's an influencer: quantifying influence on twitter," in WSDM,2011.

[4] Kayes, X. Qian, J. Skvoretz, and A. Iamnitchi, "How influential are you: detecting influential bloggers in a blogging community," in SocInfo, 2012.

[5] N. Kourtellis, T. Alahakoon, R. Simha, A. Iamnitchi, and R. Tripathi, "Identifying high betweenness centrality nodes in large social networks," Social Network Analysis and Mining, vol. 3, no. 4,2013.

[6] J. M. Kleinberg, "Authoritative sources in a hyperlinked environment," Journal of the ACM (JACM), vol. 46, no. 5, 1999.

[7] L. Page, S. Brin, R. Motwani, and T. Winograd, "The pagerank citation ranking: Bringing order to the web." Stanford InfoLab, Tech. Rep., 1999.

[8] D. M. Romero, W. Galuba, S. Asur, and B. A. Huberman, "Influence and passivity in social media," in WWW, 2011.

[9] J. Tang, J. Sun, C. Wang, and Z. Yang, "Social influence analysis in large-scale networks," in KDD, 2009.

[10] J. Weng, E.-P. Lim, J. Jiang, and Q. He, "Twitter rank: finding topic sensitive influential twitterers," in WSDM, 2010.

[11] V. Leroy, B. B. Cambazoglu, and F. Bonchi, "Cold start link prediction,"in KDD, 2010.

[12] Y. Li, J. Fan, Y. Wang, and K.-L. Tan, "Influence maximization on social graphs: A survey," TKDE, vol. 30, no. 10, 2018.

[13] J. Leskovec, A. Krause, C. Guestrin, C. Faloutsos, J. VanBriesen, and N. Glance, "Cost-effective outbreak detection in networks," in KDD, 2007.

[14] R. K.-W. Lee, T.-A. Hoang, and E.-P. Lim, "Discovering hidden topical hubs and authorities in online social networks," in SDM,2018.

[15] D. Gayo-Avello, "Nepotistic relationships in twitter and their impact on rank prestige algorithms," Information Processing & Management, vol. 49, no. 6, 2013.

[16] X. Jin and Y. Wang, "Research on social network structure and public opinions dissemination of micro-blog based on complex network analysis." JNW, vol. 8, no. 7, 2013.

[17] M. Shahriari and M. Jalili, "Ranking nodes in signed social networks," Social Network Analysis and Mining, vol. 4, no. 1, 2014.

[18] Khrabrov and G. Cybenko, "Discovering influence in communication networks using dynamic graph analysis," in SocialCom,2010.

[19] S. Aral and D. Walker, "Identifying influential and susceptible members of social networks," Science, vol. 337, no. 6092, 2012.

[20] Silva, S. Guimar˜aes, W. Meira Jr, and M. Zaki, "Profilerank: finding relevant content and influential users based on information diffusion," in SNA-KDD, 2013.

[21] Sun and V. T. Ng, "Identifying influential users by their postings in social networks," in Ubiquitous social media analysis. Springer, 2013.

[22] N. Agarwal, H. Liu, L. Tang, and P. S. Yu, "Identifying the influential bloggers in a community," in WSDM. ACM, 2008.

[23] R. Ghosh and K. Lerman, "Predicting influential users in online social networks," in SNA-KDD, 2010.

[24] Y. Yamaguchi, T. Takahashi, T. Amagasa, and H. Kitagawa, "Turank: Twitter user ranking based on user-tweet graph analysis," WISE, 2010.

[25] H. Kwak, C. Lee, H. Park, and S. Moon, "What is twitter, a social network or a news media?" in WWW, 2010.